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BCI for Music Making: Then, Now, and Next

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Chapter 10. BCI for Music Making: Then, Now, and Next

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Abstract
Brain–computer music interfacing (BCMI) is a growing field with a history of experimental applications derived from the cutting edge of BCI research as adapted to music making and performance. BCMI offers some unique possibilities over traditional music making, including applications for emotional music selection and emotionally driven music creation for individuals as communicative aids (either in cases where users might have physical or mental disabilities that otherwise preclude them from taking part in music making or in music therapy cases where emotional communication between a therapist and a patient by means of traditional music making might otherwise be impossible). This chapter presents an overview of BCMI and its uses in such contexts, including existing techniques as they are adapted to musical control, from P300 and SSVEP (steady-state visually evoked potential) in EEG (electroencephalogram) to asymmetry, hybrid systems, and joint fMRI (functional magnetic resonance imaging) studies correlating affective induction (by means of music) with neurophysiological cues. Some suggestions for further work are also volunteered, including the development of collaborative platforms for music performance by means of BCMI.

10.1 Introduction

The expression brain–computer music interfacing, or BCMI, was coined by Plymouth University's Interdisciplinary Centre for Computer Music Research team to denote BCI systems for **M**usical applications, and it has since been generally adopted by the research community (Miranda and Castet 2014). Research into BCMI involves three major challenges: the extraction of meaningful control information from signals emanating from the brain, the design of generative music techniques that respond to such information, and the definition of ways in which such technology can be deployed effectively, for example, to improve the lives of people with special needs, to address therapeutic applications, or for artistic purposes. BCMI is a growing field, with a history of experimental applications derived from the cutting edge of BCI research as adapted to music making and performance. BCMI offers some unique possibilities over traditional music making, including applications for emotional music selection and emotionally driven music creation for individuals as communicative aids. Examples of this include cases where users might have physical or mental disabilities that otherwise preclude them from taking part in music making or in music therapy cases where emotional communication between a therapist and a patient by means of traditional music making might otherwise be impossible. We assume that the reader will already have a strong understanding of the particular BCI methods documented in this chapter and their uses in other types of control signal generation. Therefore, we present an overview of BCMI and its uses in explicitly musical contexts, including existing techniques as they are adapted to musical control, from P300 and steady-state visually evoked potential (SSVEP) in electroencephalogram (EEG) to asymmetry, hybrid systems, and joint functional magnetic resonance imaging (fMRI) studies correlating affective induction by means of music with neurophysiological cues. Some suggestions for further work are also volunteered, including development of collaborative platforms for music performance by means of BCMI. The field, though small at first glance, is steadily growing, and this chapter focuses on a discrete group of research in the context of the field—inclusive but by no means exhaustive—a great variety of existing work is taking place at the time of writing. Music remains an exciting and challenging application, particularly at this time, for the BCI community.

10.2 BCI and Music, an Overview

Music can be considered the language of emotion (Lin and Cheng 2012) and shares two fundamental properties with BCI, more generally, communication and interaction. Music facilitates communication from the composer to the audience of listener/s, and interaction between an individual performer and other musicians, as well as interaction between the performer/s and the audience of listener/s. Listeners do not need any special musical education to understand communication made by musical means (Bailes and Dean 2009; Bigand and Poulin-Charronnat 2006). The dream of many musicians, particularly musicians who also engage in composition activity, is to be able to bypass the physical intermediary in the process; that of notation or transcribing ideas for subsequent performance. Highly talented musicians are able to do this to some extent through improvisation; they create and perform at the same impulse. However, this requires a significant degree of musical training and becomes infinitely more complex when other musicians are also involved. BCI offers the possibility of directly translating thought to performance in music making. We consider this *mapping* and will refer to it throughout this chapter according to the definition that mapping encompasses the process of bridging particular BCI data with auditory cues. These cues might be musical notes, complete pieces of prerendered music, smaller sound stimuli such as noises or test tones, or specific auditory filtering processes (frequency or time domain-based effects, such as frequency equalization, phasing, reverberation, dynamic time warping, etc.). An overview of different types of music mapping from complex biomedical data and subsequent evaluation strategies is given in Williams (2016). In layman's terms, one might consider a BCMI goal to be, for the user, "Think of a tune," and as you do so, the BCMI mapping would transcribe your thoughts into musical notation, or perhaps synthesize them directly as audio. Therefore, the evaluation strategy can be relatively simple in such a case. A further level of complexity might be achieved if the system could automatically generate accompaniment or other instrumentation on the fly, requiring more complex evaluation. Beyond traditional music making (i.e., composition and performance), the possibility of adapting BCMI to patients with physical disabilities who might otherwise be unable to participate in music making is clear (Miranda et al. 2011). However, BCMI systems remain a long way from this goal at the time of writing.

The use of BCI for music has steadily been gaining traction over the past three decades. Yet, before this, early pioneers made use of the EEG to generate control data for musical performance. Alvin Lucier's 1965 piece *Music for Solo Performer* (Lucier 1976) distributes amplified alpha waves around a real-world performance space, in which various types of percussion are triggered or stimulated by the amplified waves as the performer mediates their mental state by meditating and increasing the corresponding alpha wave output. The otherworldly effect was well suited to the experimental avant-garde composition movement of the time, such as the work of John Cage and contemporaries, whom Lucier had seen some years prior and would have likely been influenced by. David Rosenboom continued the early exploration with the release of *Brainwave Music* (1974), adapting the sensor/mapping strategy to incorporate biofeedback in the compositional process (Rosenboom 1990; Teitelbaum 1976). Much of this period of BCMI evolution can be characterized by the realization of the control of alpha in a participant and the subsequent adaptation of this control to music creation. The concept of adaptive biofeedback was explored by Eaton (1971), who combined visual and auditory stimuli in a manner that facilitated much of the later design of BCMI. Historically, BCMI systems would not seek to extrapolate direct meaning from brainwaves but rather force a semantic mapping between the stimulus and the generated musical output. The principal distinction is that the influence of music on brainwaves and other physiological readings might also be harnessed as some form of control signal to facilitate musical interaction. Should the system for musical interaction be designed with this in mind, the subsequent feedback loop could create useful applications in and of itself, for example, in the context of music therapy. Music therapy is a psychological therapy technique that aims to facilitate communication and improve the emotional state of a patient via musical interaction with the therapist (Aigen 2005). A typical session might involve a patient performing on an instrument in solo or in a duet with the therapist. A BCMI system might be useful for such work by facilitating patients who are not musically confident or competent enough to engage in traditional music-making activities as part of the therapeutic process, for example, performing or improvising new music that might otherwise be restricted by age or previous experience (Clair and Memmott 2008; Fagen 1982; Hanser 1985).

Significant progress toward functional BCMI was made in the 1990s in systems such as *Biomuse* (Knapp and Lusted 1990), which mapped the acquisition of low-level neuroelectric and myoelectric signals to the generation of musical structure in MIDI format in real time, after applying statistical feature extraction to the captured signals. This system also used other physiological readings, including eye tracking, muscle tension, and real-time audio input, and as such could be considered a "hybrid BCMI."[*] At the time of publication, the creators of Biomuse directly acknowledged the possibility of adapting this technology to paralyzed or otherwise movement-impaired individuals, in order to give them access to music making—which in and of itself has been known to be a therapeutic process (Aldridge 2005; Hanser 1985)—and thus the importance of BCMI systems that only require brainwave control becomes clear in cases where the intended end user might be physically paralyzed such as "locked-in" patients (victims of amyotrophic lateral sclerosis or motor neurone disease).

Figure 10.1 shows an overview of a generic BCMI. This signal flow diagram can be applied to most BCMIs. Typically, a real-time input is analyzed and subjected to some signal processing. The exact processing varies; it could be as simple as filtering or a more complicated statistical reduction such as principal component analysis. Machine learning techniques are now becoming common for adaptive processing of control signals for music generation and performance (AlZoubi et al. 2008, 2009; Kirke et al. 2012, 2013). In such cases, the processed signal is used as a control signal to inform mapping to musical structure, or a specific range of musical features that might combine to make a musical structure of

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[*] See Section 10.4 for the distinction between this and a BCMI that combines both active and passive control solely from brainwave input.

some description (note that this is not necessarily “music’ at this stage of the process). An overview of specific mapping techniques for digital instrument design is given by Goudeseune (2002). Various combinations of mapping strategies exist, including one-to-one, one-to-many, and many-to-many combinations (Hunt and Kirk 2000). Typically, the mapping is predetermined at the stage of system design, but an adaptive mapping is indicated in this figure by the dashed lines (systems that use neurofeedback to adapt in this manner are discussed later in this chapter). It is in the mapping stage that most BCMIs derive their variety. Both the format of the output and the particular individual musical features and ratios between filtered control signal and given musical feature are valid, and many different types of mappings have been experimented with (Brouwer and van Erp 2010; Chew and Caspary 2011; Daly et al. 2014c). The linear mapping of alpha waves to particular acoustic instruments in *Music for Solo Performer* is significantly different to the mapping in later systems such as Miranda’s BCMI, which maps the control signal to the control of amplitude of specific musical sequence playback (Miranda 2010). Further variety can be given at the performance stage; oftentimes, BCMI systems have been married with sound synthesis to facilitate real-time performance (Hinterberger and Baier 2005). These systems have been used to generate musical scores for human performers or to trigger playback of pre-recorded musical material from a database or library (Eaton et al. 2014). The use of the resulting musical stimulus to mediate or entrain the listeners’ brain activity (i.e., neurofeedback) is also a fertile area for research activity (Daly et al. 2014a, 2016a; Hinterberger and Baier 2005) and forms the last generic functionality shown in Figure 10.1.

Neurofeedback is becoming increasingly common in the design of BCMI for specific purposes such as the therapeutic applications described above. Recent advances in electroencephalography have made these platforms more affordable and accessible to BCMI designers. Next, we might expect to see fully realized BCMI systems that provide full control over the generation and playback of electronic music, the creation of the score for acoustic instrumental music, or multibrain systems facilitating the kinds of interactions that musicians who are used to performing in groups can already experience. This chapter will explore historical approaches first, before illustrating some of these applications to music creation and offering some suggestions as to what might happen next in the field.

10.3 Historical Approaches

Three types of BCMI approaches have been formally documented: user oriented, computer oriented, and mutually oriented approaches (Miranda et al. 2003). User-oriented approaches attempt to derive meaning directly from the input, giving the user complete control within the boundaries of the mapping. This often relies on a one-to-one mapping, as more complex mappings can be less readily interpretable by a casual user assuming the user is not also the determiner of the mapping in question. As well as the early experiments documented in the introduction to this chapter by Lucier and Rosenboom, Richard Teitelbaum demonstrated the use of a user-oriented one-to-one mapping in a BCMI in his 1967 piece *Spacecraft* (Teitelbaum 1976), which used amplified EEG as a control signal for an analog sound synthesizer in an improvised performance. One of the technical challenges to this approach is in the classification of meaning from EEG, though as many chapters of this book explore this classification process has advanced significantly in recent years. Computer-oriented systems require the user to adapt their own interactions toward the functions of the computer to achieve musical control. Most BCMI systems fall into this category. Particular frequencies might be mapped to fixed musical parameters, so that the forms are required to mediate their own brainwave frequencies to achieve the desired musical output from the system (e.g., meditating or otherwise actively controlling the state of mind to change the brainwave amplitudes and frequencies as collected by the EEG). This approach is exemplified by *Music for Solo Performer* as discussed in the introduction of this chapter, or more latterly by ensemble performance in examples by the *Biomuse Trio* (Knapp et al. 2009; Lyon et al. 2014) (see, e.g., their 2011 piece *Music for Sleeping and Waking Minds*). The third category, mutually oriented, combines both the user-oriented and computer-oriented functions, allowing a more complex degree of user control over the resulting music. Mutually oriented systems combine the functions of both user and computer orientation whereby the two elements adapt to each other, so that more sophisticated musical mappings can be inferred from the EEG data. The mutually oriented system learns an individual's responses over a time series and then creates primary and secondary mappings. This increases the likelihood of useable and accurate EEG as the input and output effectively calibrates for an individual. This was the approach used in Eaton's *The Warren*. Here, the system requires the user to learn how to generate specific commands and features mappings that adapt depending on the behavior of the user (Miranda and Castet 2014).

Various commercially available systems allow EEG detection to command musical functions, albeit often with rudimentary mapping. Two types of EEG data are common in BCMI systems, event-related potentials (ERP) and spontaneous input. The P300 ERP (or "oddball paradigm") has been used to allow active control over note selection for real-time synthesis (Grierson 2008; Grierson and Kiefer 2011) using methods that are not dissimilar to the ERP typing or spelling systems that have become more common in the BCI world but adapted to musical notes rather than text input. Stimulus-responsive input measures, for example, the SSVEP (Middendorf et al. 2000), have been adapted to real-time score selection and other controls of musical features such as volume (Miranda 2010). One system developed by Miranda and colleagues made use of such measurement from the visual cortex in response to flashing stimuli and subsequently mapped these to particular selections of pre-composed musical score. Users were able to make the selection by focusing their gaze on a particular icon flashing at a given rate. The system looked for amplitude changes across the four frequencies presented as visual stimuli and then correlated these amplitude changes to musical feature selection. A second level of control was also shown to be useful and possible in the system as the amplitude response in the corresponding wave could gradually increase in proportion to the duration of the viewers' gaze, thereby giving mapping control for musical features that were not linear (e.g., volume control of a particular passage or instrument). This combination represented a breakthrough in that real-time explicit control of a BCMI was shown to be practical, albeit with a limited selection of musical mappings. A photograph of the system in performance is shown in Figure 10.2. For a full treatment of this process, and others like it, the reader is referred to Eaton and Miranda (2014). Whether this specific example should be classified as a "pure" BCI or not could be the subject of some debate as the interface required an EEG interpretation of eye position, rather than explicit brainwave-only measurement.

There is a marked difference between systems for direct musical control by means of BCI, as documented above, and systems for *sonification* or *musification* of brainwave data (typically EEG) (Baier et al. 2007a,b; Hinterberger and Baier 2005). Sonification is a process whereby data are directly transmitted by auditory means:

> Sonification conveys information by using non-speech sounds. To listen to data as sound and noise can be a surprising new experience with diverse applications ranging from novel interfaces for visually impaired people to data analysis problems in many scientific fields (Toharia et al. 2014).

Sonification in biomedical applications is a growing and progressive field, with many existing mappings from EEG (Väljamäe et al. 2013). The distinction between *sonification* and *musification*, both related forms of auditory display, is that in a *musification*, the data are not just auralized linearly, but instead, various constraints are created and applied in order to create a musical performance of the sonic data. This is an indistinct line and not easily delineated, but essentially the complexity and intent of the mapping involved determine whether the BCMI system is sonifying or musifying in its output. One example of EEG musification applied the rate of alpha to the cadence of the rhythm structure in a music segment, while mapping the variance of EEG to chords in a bar and the amplitude of waves to the note position of a melody (Wu et al. 2010). Rhythm is an interesting musical property with specific brain cortex associations (Baier et al. 2007c) and, as such, has also been utilized in EEG analysis of musical rhythm, for example, in the evoked gamma band (20–60 Hz) by rhythmic tone sequences (Snyder and Large 2005). However, evaluation strategies for such mappings, and musification in general, are not universally agreed upon and remain a significant area for further work. Nevertheless, musification allows the listener to engage with complex data in an intuitive way by exploiting their everyday listening experiences in the real world. This philosophy is common to many auditory display projects making use of multimodal techniques in the biomedical arena.

> The idea behind sonification is that synthetic non-verbal sounds can represent numerical data and provide support for information processing activities of many different kinds (Mihalas et al. 2012).

The limitation is somewhat dependent on the complexity of the mappings and the number of meaningful, controllable features that might be extracted from the EEG. This might include overall EEG amplitude, the amplitude of specific frequencies, or the amplitude of frequencies at specific electrode placements on the scalp including dependent measures such as the level of asymmetry between electrodes on opposite sides of the cortex (Kirke and Miranda 2011).

The simplistic level of control available with direct mapping has led to the adoption of more complicated mapping strategies—that is, many-to-many—where algorithmic composition techniques are correlated with specific control signals. Melodies might be controlled by comparing alpha and beta amplitudes across given electrodes, or rhythmic properties adapted from a probabilistic algorithmic composition system (Miranda and Soucaret 2008). This mapping has also been reversed, wherein the rhythmic properties of the resulting material are directly controlled by the BCMI (Daly et al. 2014c). In such systems, there is a separation between cognitive control and the deliberate mapping of algorithmic composition techniques or other generative music techniques in semantic response to this control. Music is perhaps particularly well suited to the presentation of brainwave states in this manner, given the parallels in temporal nature between the two mediums. See Figure 10.3 for an example of SSVEP in use for score selection in real time.

10.4 Current: Hybrid Systems and Affective State Control

The historic systems presented in the section above can be broadly separated into two types: those that offer active control, wherein the user makes deliberate cognitive choices that are then mapped to musical features, and passive control, wherein BCI is used to determine subconscious mental states that are then used to inform the musical feature mapping. Hybrid systems combining both approaches simultaneously are also possible, though it is important to make a clear distinction between these types of hybrid systems and hybrid systems that combine different types of input sensors, for example, combining acoustic features with EEG, or combining other biophysiological readings such as heart rate or galvanic skin response with EEG (Daly et al. 2014b, 2015b). One of the earliest examples of such a performance can be seen in Richard Tietelbaum's *In Tune* (1967), which combined two EEG inputs with hearbeat and breathing sensors, to create one-to-one computer-oriented mappings for a musical performance (giving the users control of on and off switches and amplitude envelopes as they were passed to an analog sound synthesizer). Systems that combine both active and passive control might use passive affective state detection in combination with a degree of active control, for example, as afforded by the linear amplitude response of SSVEP as described above.

Collaborative music generation has a rich history (Le Groux and Verschure 2009; Manzolli and Verschure 2005). The ability of BCI to determine affective states and the ability of music to communicate emotions suggest that ***a***ffect-driven BCMI (*a*BCMI) could be a logical multidisciplinary application toward collaborative music making. One such example provides the ability for two users to collaborate—collaboration is one of the central tenets of ensemble music performance—by mapping BCI measures of affect to the control of amplitude of two separate musical features (Leslie and Mullen 2012). This aspect of collaboration is perhaps one of the most exciting outcomes of BCMI. Subsequent measures of detecting different levels of emotional states have been adapted to musical control by Ramirez and Vamvakousis (2012), who evaluated a database of emotionally charged sound stimuli by means of EEG analysis across a two-dimensional affect space. Russel's two-dimensional space (Russell 1980) is commonly, but not exclusively, used in emotional assessment of musical stimuli. These mappings have also been exploited by computer-aided composition systems, with the suggestion that such systems could be driven by neurophysiological readings from BCI in *a*BCMI implementations (Williams et al. 2014).

Measurement of affective state changes in response to music takes its lead, as in most other cases of BCMI development, from the startling advances in BCI, in this case in defining affective (emotional) states from EEG (Chanel et al. 2006, 2007). The distinction is that emotional responses to music can be state dependent or independent in the same way that BCMI systems might be user or computer oriented—in other words, an emotional response *to music* (Lin et al. 2010). The ability of music to communicate emotions makes affective state measurement in order to inform musical feature selection a particularly strong candidate for BCMI applications. Recent research has highlighted a number of benefits when emotionally charged music is used to improve the listeners' cognitive performance (Franco et al. 2014). A significant amount of further work remains in quantifying listener responses to affectively charged music and in measuring the impact on a given affective state that music might have, as individual preferences and other environmental factors such as cultural expectations and musical training make emotional responses to musical stimuli highly variable (Scherer 2004). Nevertheless, the possibility of developing affectively responsive BCMI means that these individual variations might be mediated by BCI technology in ways that had previously been thought impossible by musicologists and music psychologists.

An example of affective state mapping to musical feature selection can be seen in the world of musical information retrieval (Eaton et al. 2014; Lin and Cheng 2012). Here, affective state measures are adopted from the mainstream BCI world and used to select music from a database that has already been tagged with emotional descriptors ("calm," "energetic," "happy," "sad," etc.). There is an interesting point to be made while determining listeners' emotional responses to certain types of music, because "sad" music has been shown to be enjoyable in some cases (Vuoskoski and Eerola 2012; Vuoskoski et al. 2012) and indeed to have similar neural correlates when measured by EEG (Daly et al. 2014b). It is also important in such work to acknowledge the difference between "perceived" and "induced" emotions. *Perceived* emotions refer to the emotional meaning the listener *understands* the music is supposed to convey, while *induced* responses refer to the emotion, or emotions, actually *felt* by the listener while listening (Juslin and Laukka 2004). In this manner, a piece of music may be perceived as intending to communicate "sadness" by the listener, while at the same time giving them a pleasurable feeling (i.e., they enjoy listening to the sad music). This seeming paradox has been well explored in musicological research (Hunter et al. 2010; Huron 2011; Manuel 2005). The ability of music to match or influence a listener's emotions has been exploited by, among other disciplines, music therapy, facilitating communication and improving the emotional state of a patient via musical interaction with the therapist. By enabling the generation of music that matches the emotional state of a patient, an *a*BCMI might potentially be of use as an expressive tool for patients to express their emotional state to the therapist regardless of physical ability or communicative handicap, for example, patients with autism, Asperger's syndrome, or even locked-in patients with little or no physical mobility.

The theoretical advantage of this approach over conventional music therapy approaches is that the BCMI is able to directly monitor the users' emotional state via physiological indices of emotion, which have the potential to be more robust and objective measures of emotion than user reports or even the expertise of the music therapist. Finally, the design and implementation of a successful *a*BCMI for music therapy might also facilitate modulation of a user's emotion by means of an affective feedback loop. This application would be unique to an *a*BCMI—which might, for example, generate music that gradually improves the mood of the patient in an autonomic process without the need for a therapist (Daly et al. 2014b, 2016b).

10.5 Next Steps

This chapter has presented a brief overview of the growing field of applications harnessing the power of BCI for music. From a somewhat fantastical science-fiction plot just a few decades ago to real-time control of musical feature generation for synthesis or playback by real musicians, the dream of going from imagining music to hearing it performed instantly, along with all of the benefits that such a realization might bring for patients with particular physical disabilities or those in music therapy practice, is drawing ever closer.

Tentative steps toward biofeedback from the 1960s and 1970s where alpha band control from EEG was exploited for one-to-one computer-centered BCMIs have exploded after the advances in other BCI technology, to accommodate affective state measurement, multiple user interfaces, a degree of live performance, and hybrid systems that combine both active and passive control, as well as hybrid systems that accommodate other physiological readings. A move toward *a*BCMI, affectively driven brain computer music interfacing, suggests that a freedom to explore the creative possibilities afforded by music, including emotional contagion, communication, and perhaps, most importantly, *interaction* with others, is on the near horizon in a developmental and commercial sense. It is fair to say that BCMI does not contribute enormously to the development of new BCI technologies in the main, being an engineering problem of implementation rather than advancement. On the other hand, significant advances in understanding particular responses that are only inherent in listening—for example, the emotional difference in 2D between "angry" and "afraid" sounding music, both of which would be classified traditionally as high arousal and low valence, yet both of which would encapsulate markedly different types of music regardless of an individual's listening preferences—suggest that BCMI still has something to offer to both neuroscience and the BCI community in general. The distinction between perceived and induced emotion is one that is still challenging. While visual examples can help differentiate this, music offers perhaps one of the strongest ways to explore this affective phenomenon. The temporal nature of music also lends itself well to illustrating the changing pattern and transient nature of emotions and many neurophysiological responses in general.

A tangential, but very related area to this chapter is the burgeoning field of work using non-nervous physiological signals, such as heart rate, galvanic skin response, and so on. It would be remiss not to speculate on the possibility of combining such work with BCMI in a sensor-fusion setting, especially given recent advances in biosignal interfacing for music making (Daly et al. 2015a; Nirjon et al. 2012; Pérez and Knapp 2008). However, it would be almost impossible here to explore the full range of possibilities afforded by BCI for music making as conducted to date, without looking to other biosignal interfacing. Nevertheless, looking to the future, one area that this chapter has not yet been able to explore in the context of neurophysiological interfacing is the future application of joint studies combining fMRI with EEG. This is particularly relevant to music given the spatial resolution issues that are currently inherent with EEG work. fMRI studies have been shown, in the context of affect measurement and, thus, subsequent *a*BCMI design, to be particularly useful in measuring and estimating induced affective states; yet, in a standalone context, they are not often employed by BCMI research. This is partly a practical concern of course not only because of the cost and size of facilities required but also partly because of the temporal resolution being inherently problematic when specific listening tasks are concerned. Musical features can often change radically in the duration of a second or two, which can be the smallest possible frame size afforded by some fMRI studies. Nevertheless, despite these concerns, fMRI does provide for a much greater spatial resolution for real-time musical control and adaptation. A combined approach comparing EEG and fMRI results to the adaptive control of music generation for affective induction has been proposed and is the subject of recent trials (Daly et al. 2016a; Miranda 2010). We may then, in the future, see these trials and other work like them be adapted to more generalizable portable models that might be controlled by EEG, using adaptive mappings derived by machine learning rather than prescribed by the designers of such systems, for musical collaboration regardless of physical ability or previous musical training. Anyone who has played an instrument in isolation will know that here, in the process of *collaboration*, might BCMI's real future lie.

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Figure 10.1 Overview of a generic BCMI. Most systems are differentiated by the mapping, which is typically fixed at the point system design but in the future might be adaptable to neurofeedback.

Figure 10.2 SSVEP-based performance of a string quartet, under the active control of four patients with varying degrees of locked-in syndrome. Here, the patients perform "Activating Memory" (Eduardo Reck Miranda), a composition for eight performers: a string quartet and a BCMI quartet. In this performance, four severely motor-impaired patients at the Royal Hospital for Neurodisability (RHN), London, UK, use BCMI technology to generate musical scores in real time for the string quartet to play.

Figure 10.3 Score being generated in real time according to SSVEP selection. Taken from the documentary film of "Activating Memory" by the Paramusical Ensemble at the RHN on July 17, 2015, directed by Tim Grabham.